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Stimulating Agricultural Technology Adoption

Lessons from Fertilizer Use among Ugandan Potato Farmers

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Contents

Tables

ABSTRACT

In the context of a growing population in an already densely populated area, agricultural yields will need to increase without putting additional stress on the environment. The adoption of modern inputs by smallholders is an important ingredient of agricultural transformation. In this study we explore plot-level, household-level, and institutional-level characteristics associated with agricultural technology adoption behavior among smallholder farmers. The aim is to uncover correlations that can guide the design of policies and incentives that are likely to increase adoption. We explicitly differentiate between fixed costs that are likely to affect the decision to use the technology and variable costs that are more relevant for the decision regarding use intensity. In addition, we examine how the importance of each of these characteristics differs with asset status. To do so, we use data from about 1,880 potato plots cultivated by 500 randomly selected potato growers in southwestern Uganda. We first categorize households into poorly endowed and well-endowed asset classes based on their access to productive assets. We then estimate double-hurdle models for take-up and use intensity of fertilizer for each group. The results show that the factors associated with the decision to use fertilizer are often different from those associated with the decision about how much fertilizer to use and that the characteristics correlated with fertilizer adoption differ between asset-poor and asset-rich farmers. For instance, asset-poor female-headed households are less likely to use fertilizer, but if they do, they use more of it than male-headed households. Our results also suggest fertilizer packaging and distribution are important factors in fertilizer adoption decisions due to their impact on costs related to both indivisibilities and uncertainty about the quality. We derive a range of policy recommendations.

Keywords: double-hurdle model, fertilizer, technology adoption, potatoes, Uganda

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1. INTRODUCTION

During the next few decades, agricultural productivity will have to increase substantially, especially in areas where productivity is relatively low, such as in Africa south of the Sahara. Population is projected to increase to more than 9 billion by 2050, and a growing middle class and rapid urbanization lead to increasingly calorie-intense and complex diets. Globally, food production will need to increase by about 70 percent between 2005 and 2050, and this will have to be accomplished against the backdrop of increasing competition for land, water, and energy and in the context of a changing climate. Also in Uganda, a country with one of the highest fertility rates in the world located in an already densely populated area, food production has barely kept up with demand, and this has mainly happened through expansion of land under cultivation and shorter fallow periods. In the long run, such a strategy is clearly not sustainable: crop yields, defined as the amount of the crop produced per area of land (and commonly measured in [metric] tons per hectare), will have to increase substantially.

Sustainable intensification, involving the use of modern inputs such as inorganic fertilizer and hybrid seeds, and recommended agricultural practices such as irrigation and row planting are frequently advocated as the best ways to increase crop yields (Tilman et al. 2011). Agronomic studies find substantial yield gaps, with most crops yielding only a third of their potential yield when modern inputs and recommended practices are used. In Uganda, use of modern inputs, especially inorganic fertilizers, is low, and hence there is considerable scope to increase yields through intensification. Only about 36 percent of households use any form of fertilizer on any potato plot (Van Campenhout, Bizimungu, and Birungi 2016). The yield gap for potatoes is about 75 percent, and using good seeding materials and applying inorganic fertilizer according to recommendations increases potato yields from 6.4 tons per hectare to 16.5 tons per hectare (Walukano et al. 2016).

Despite these potential gains, not all households engage equally in crop intensification, suggesting costs and benefits related to fertilizer use affect households in different ways. To better understand why some households adopt certain technologies while others opt out, it is instructive to compare adopters to nonadopters on a range of characteristics that may be correlated to these decisions. Potential factors that may be related to the adoption of a modern input or technology include farm-level characteristics such as household composition and the education level of household members. Adoption decisions also may differ conditional on a range of institutional and access-related variables, such as the price of fertilizer, market access, distance to a farm supply store, and access to extension. Finally, the use of modern inputs and recommended agricultural practices also may vary by plot-level agroecological variables such as plot size and topography.

This research will investigate how the importance of these characteristics varies over two dimensions. First, we will differentiate between two parts in the decision process to adopt a certain technology. In most cases, such as in the case of fertilizer adoption, it is first decided whether to use fertilizer. Only in a second stage, conditional on this first decision, is the decision made about how much to use. We allow the coefficient estimates of the plot-level, household-level, and institutional-level characteristics to differ between these two steps. Second, we suspect that the access a household has to productive assets will influence the relative importance of these characteristics and therefore allow for differences between asset-poor and asset-rich farmers as well.

This paper contributes to the literature that attempts to better understand agricultural technology adoption. One strand of the literature aims to identify the causal impact of particular determinants of technology adoption using field experiments. For instance, Duflo, Kremer, and Robinson (2011) look at the role of farmers' failure to commit themselves to fertilizer use in Kenya. Karlan et al. (2014) investigate the relative importance of liquidity constraints and risk consideration in technology adoption. For a recent overview of this literature, we refer to de Janvry, Sadoulet, and Suri (2016). This study takes a more comprehensive approach, viewing technology adoption as a complex process involving various interacting push and pull factors. For instance, we expect technology adoption to be sustained only if the household has both access to inputs and access to a market for its produce. This research is therefore closer to the body of literature that tries to understand the decision to adopt technology using observational data using binary choice models (Marenya and Barrett 2007). Only recently, studies also have started considering adoption intensity (Ricker-Gilbert, Jayne, and Chirwa 2011). In most studies, asset endowments are simply included as an additional determinant in the regression models instead of interacted with other determinants. In this study, we follow Langyintuo and Mungoma (2008), who argue that technology adoption may structurally differ according to asset levels, and we therefore estimate separate models for asset-poor and asset-rich farmers.

For the empirical application, we rely on cross-sectional data from 489 potato farmers cultivating about 1,880 plots located in southwestern Uganda. The households were first categorized into two groups—asset-poor and asset-rich households—based on their access to productive assets. Following Filmer and Pritchett (2001) and Zeller et al. (2006), we aggregate household productive assets to construct asset indexes using principal component analysis (PCA). We then use a double-hurdle (DH) model to account for the two-stage decision process to adopt and use inorganic fertilizer. The first hurdle models the decision about whether to adopt fertilizer. The second hurdle models the decision about the quantity of fertilizer to apply per hectare, conditional on the decision made in the first stage of the model.

Our results confirm the importance of differentiating between the adoption decision and the decision regarding use intensity. Access to labor appears to influence the decision to adopt but not the decision about the quantity applied. The fact that farmers with larger plots are more likely to adopt fertilizer suggests substantial fixed costs. The price of fertilizer as well as access to credit becomes relevant only when the decision related to the quantity applied has to be taken. We also find interesting differences between asset-rich and asset-poor farmers. Female-headed households are less likely to adopt but only in that they are also asset constrained. More manpower seems to be correlated to adoption only among the asset rich.

The rest of the paper is organized as follows. Section 2 outlines a simple conceptual framework to help us think about agricultural technology adoption in the context of smallholder farmers. This is followed by a section that presents the empirical methods. In particular, it explains PCA, which will be used to differentiate between the asset poor and the asset rich. In addition, it presents the DH model that will be used to model both the decision to use fertilizer and, conditional on this decision, how much fertilizer is applied. Section 4 explains what variables we will include as potential correlates, taking clues from the literature on agricultural technology adoption. In Section 5, we briefly describe the context for the empirical application. The next section outlines data preparation and provides descriptive statistics. Section 7 presents the estimation results. The paper concludes with some policy implications for stimulating adoption of fertilizer use in Uganda.

2. CONCEPTUAL FRAMEWORK

A simple conceptual framework may help fix ideas about agricultural technology adoption among smallholder farmers. The main building blocks of the framework are related to the costs that come with technology adoption on the one hand and access to productive assets by the farm household on the other hand. Thinking about agricultural technology adoption in terms of these two dimensions will guide us to a particular empirical strategy, where the adoption process is broken into two sequential decisions and is conditioned on household asset holdings.

In general, adoption of improved agricultural technologies involves both fixed and variable costs. For instance, new technologies often require considerable learning costs, through public agricultural extension services, through careful observation of and interaction with peers, or through experimentation. Sometimes complementary tools need to be purchased to apply the technology. Such an initial investment is often substantial for poor households and may act as a fixed cost that prevents households from adopting, even though the technology itself is affordable. For example, the cost to cover the distance between the farm and the fertilizer supply store is likely to be an important factor in the decision to start using fertilizer, irrespective of the cost of the fertilizer itself.

In addition to fixed costs, there are costs that are a function of the scale at which the technology is adopted. Examples here are the cost of a kilogram of fertilizer, the cost of a bag of seed, and the cost of labor needed to apply the fertilizer or complementary inputs that are scale dependent. These costs are less relevant for the decision to adopt but are likely to play an important role in the decision about the use intensity of the technology. For instance, the price of fertilizer is likely to be an important element in the decision about how much fertilizer to use, irrespective of the cost to cover the distance between the farm and the fertilizer supply store.

The costs related to technology adoption are influenced by a range of plot-, household-, and institutional-level characteristics. The role played by these characteristics also will depend on what type of costs they affect most. One particular characteristic may affect the fixed cost related to technology adoption more than another characteristic that may be more important for variable costs (Ricker-Gilbert, Jayne, and Chirwa 2011). Therefore, it will be instructive to break the technology adoption into two different yet related aspects. In one model, the decision to adopt is explored, and in a second separate but related model the decision about the scale of adoption is modeled. We will see in the next section that this can be done conveniently with a DH model.

The second building block of our conceptual framework relates to the level of productive assets available to the household. These asset levels also may affect the adoption process. This can be done directly when productive assets serve as complements in the technology adoption process. However, assets also often serve as a buffer against risk exposure, indirectly influencing technology adoption. Examples of complementary assets include mobile phones that can be used to obtain information about technology adoption or vehicles that can be used to transport fertilizer from the store to the farm. Livestock assets, on the other hand, are often thought to be an important risk-coping mechanism (Fafchamps, Udry, and Czukas 1998). To get a better idea of the structural differences in which asset levels interact with characteristics at different levels, we will separately model adoption of asset-rich and adoption of asset-poor farmers.

While the conceptual model above connects different costs to different stages in the decision process, the reality is often more complex. For instance, as fixed costs often need to be spread over space, fixed costs also may influence the scale of technology adoption. Or for some households, the variable cost may be too high to adopt even at a very small scale. Similarly, in reality the two roles of assets may be difficult to separate, and some assets may be complements that make the technology adoption process itself less risky. For example, irrigation may make fertilizer more effective and at the same time may make the returns to fertilizer less risky.

3. EMPIRICAL METHODS

In this section, we first explain how various assets are aggregated into a single asset index using PCA. We then present the DH model, which we will use to describe the process of fertilizer adoption.

Estimating the Asset Index

As we want to compare exogenous characteristics related to adoption of asset-poor and asset-rich farmers, we first need to categorize farmers into these two groups. We will do this by first agreeing on an asset indicator that can be used to rank households from lowest asset levels to highest asset holdings. We will then decide on a cut-off point below which households are classified as asset poor and above which households are classified as asset rich.

Productive assets is a broad concept that comprises various assets classes and categories, ranging from farmland to livestock assets and wheelbarrows to mobile phones. It is not a priori clear which assets are relevant from both an economic and a statistical point of view. In principle, it is possible to simply estimate the value of each asset a household possesses and then add up all these values to come to the total value of assets. However, it is often difficult to get prices for assets, and imputation is often not straightforward. In addition, simply adding all assets gives equal weight to all asset classes, while we may want to give more weight to asset classes that are more informative to rank households.

Following Filmer and Pritchett (2001), Zeller et al. (2006), Langyintuo and Mungoma (2008), and Ghimire and Huang (2015), this paper uses PCA to rank households from asset poor to asset rich. PCA is a popular method used for data reduction. When multiple, possibly correlated measures for the same process are available, PCA transforms these variables into a smaller number of uncorrelated variables. The components are ordered such that the first component explains the largest possible amount of variation that is common to all variables in the original data (Filmer and Pritchett 2001). Since PCA is sensitive to the scaling of the variables, it is also common practice to convert all components into standardized variables with a mean of 0 and a standard deviation of 1 (Zeller et al. 2006). Hence, the resulting index is also a normally distributed variable with a mean of 0 and a standard deviation equal to 1. Using the weights derived from PCA, a household-specific asset index can be computed based on each household's indicator values. This index can then be used to rank the households.

Cragg's DH Model

Similar to semisubsistence farmers' decision processes to sell (part of) their harvest, agricultural technology adoption processes are assumed to involve two decision stages (Bellemare and Barrett 2006; Xu et al. 2009; Noltze, Schwarze, and Qaim 2012). First, the farmer decides whether to adopt a particular new technology or practice, and second, conditional on having decided to adopt, the extent of adoption or use intensity is determined. In the case of fertilizer adoption, it is thus first decided to use fertilizer or not, after which a quantity (kilograms per hectare) is decided on in a second stage.

In general, the decision process above results in a situation wherein not all the farmers will adopt fertilizer. As such, in the data, many observations will have zero values for the quantity of fertilizer applied. In such a scenario, when observations are piled up at a censoring point, the standard Tobit model originally formulated by Tobin (1958) is appropriate. However, to model a two-step process, the Tobit model is fairly restrictive because it requires that the process that generates the zeros be the same as the process that generates the positive outcomes. In other words, it assumes that the decision to purchase fertilizer and the amount purchased is determined by the same underling process. Econometrically speaking, the vector of coefficient estimates on the decision to adopt and the quantity adopted is assumed to be one and the same.

The DH proposed by Cragg (1971) is more flexible than the Tobit model because it accounts for the possibility that the factors influencing the decision to use fertilizer and the factors influencing the decision about the quantity of fertilizer may be different. Referring to the conceptual framework in the previous section, it may be that certain characteristics influence fixed costs related to adoption, but once the decision to adopt has been made, these characteristics may affect the quantity purchased much less. The DH model allows the same variable to affect adoption and use intensity in different ways.

The DH model has been gaining importance in research related to household-level decision making in agricultural economics. Studies on sequential decision making in particular have abandoned the Tobit model in favor of the DH model. Especially since Bellemare and Barrett's (2006) seminal paper that demonstrates that smallholder market participation is best described by a sequential process whereby households first decide whether to sell or buy and only then decide on the quantities, double- and even triple-hurdle models have become the preferred model in empirical case studies on smallholder market participation (for example, Mather, Boughton, and Jayne 2013; Olwande et al. 2015; Burke, Myers, and Jayne 2015). Decisions related to modern inputs or technology follow a process similar to smallholder market participation decisions. For instance, in the case of fertilizer, the decision about whether to use fertilizer is taken first, and conditional on this decision, a second decision about the quantity of fertilizer is taken (Ricker-Gilbert, Jayne, and Chirwa 2011). In the case of improved seed varieties, the decision is first taken to switch from local to improved sees, after which a decision is taken about the quantity of seeds (Langyintuo and Mungoma 2008; Ghimire and Huang 2015). Bokusheva et al. (2012) use a DH model to investigate the adoption of improved storage technologies.

In the DH model, a different latent variable is used to model each part of the decision process. In the first hurdle, a probit model is estimated to determine the probability that a farm household will adopt fertilizer (y_1), and in the second hurdle, a truncated normal model is used to determine the extent or intensity of adoption, measured as kilograms of fertilizer used per hectare (y_2). Each hurdle is conditioned by the household's socioeconomic characteristics, institutional and access-related variables, and agroecological variables (x). However, as the latent variables may be determined differently by these variables, we allow the vector of coefficient estimates to differ between the two parts in the decision process and define $y_1 = x'\alpha + \varepsilon$ and $y_2 = x'\beta + \epsilon$, where ε is the error term associated with the probit part of the model ($\varepsilon \sim N(0,1)$) and ϵ is the error term related to the truncated normal part of the model ($\epsilon \sim N(0,\sigma)$). Estimating the DH model then involves maximizing the following likelihood function:

$$\ln(y|x) = \prod_{y=0}\left[1-\Phi\left(\frac{x'\alpha}{\sigma_\varepsilon}\right)\right]\Phi\left(\frac{x'\beta}{\sigma_\epsilon}\right) \times \prod_{y>0}\Phi\left(\frac{x'\alpha}{\sigma_\varepsilon}\right)\Phi\left(\frac{x'\beta}{\sigma_\epsilon}\right)\frac{\phi[(y-x'\beta)/\sigma_\epsilon]}{\sigma_\epsilon\Phi(x'\beta/\sigma_\epsilon)} \tag{1}$$

where ϕ and Φ are the density and cumulative density functions of the normal distribution and σ_ε and σ_ϵ denote the standard distribution of the respective error terms.

To ease interpretation of the results, we also provide estimates of the partial effect of the independent variables around the probability that $y_1 > 0$ as is customary in a standard probit analysis. In addition, since separability in estimation does not imply separability in interpretation, we follow Burke (2009) and provide estimates of the partial effects of the included independent variables on the unconditional expected value of y_2. Standard errors for these estimates are obtained through a bootstrap procedure that allows for clustering at the household level. In the interest of space, we do not report the (conditional) marginal effects of the independent variables around the mean of y_2, as they are virtually equal to the coefficient estimates obtained from equation 1. We estimate the model at the plot level, as Noltze, Schwarze, and Qaim (2012) suggest plot-level data are important to understand the adoption of system technologies.

4. VARIABLE SPECIFICATION

We selected explanatory variables on the basis of the recent adoption literature and organized them into three broad categories: farm-household-level characteristics, institutional and access-related variables, and plot-level agroecological variables. In particular, we base our study on Bokusheva et al. (2012), who study the determinants of the adoption of improved postharvest storage technology for staple grains in Latin America; on Feleke and Zegeye (2006), who study the determinants of the adoption of improved maize varieties in southern Ethiopia; on Ghimire and Huang (2015), who look at the determinants of the adoption of improved maize varieties in Nepal; on Langyintuo and Mungoma (2008), who study the adoption of improved maize in Zambia; on Marenya and Barrett (2007), who study adoption of improved natural resources management practices among Kenyan farmers; on Mariano, Villano, and Fleming (2012), who study adoption of modern rice technologies and good management practices in the Philippines; on Noltze, Schwarze, and Qaim (2012), who study the adoption of a system of rice intensification in Timor Leste; and on Teklewold, Kassie, and Shiferaw (2012), who analyze the adoption of multiple sustainable agricultural practices in rural Ethiopia.

Farm Household Characteristics

Farm household characteristics included age, gender, and education level of the household head; household size; and the proportion of females within the household. It is believed that with age, farmers accumulate more knowledge and are better able to exploit social networks, rendering innovations less risky and reducing information inefficiencies. However, older farmers are thought to be less amenable to change and therefore less willing to change from their old practices to new ones. As farmers age, their planning horizons also may shrink, reducing incentives to invest in the future (Marenya and Barrett 2007). Younger farmers are often thought to be more flexible and interested in trying out new things. They are also more likely to be conversant with new communication technologies, which often are used to disseminate agriculture-related information these days (Aker 2011). Their relative lack of experience also means there is a lower opportunity cost to learning new technologies, compared to older, more experienced farmers. Therefore, some argue younger farmers are more likely to adopt new technologies. At the same time, younger farmers may be inherently less patient or at a point in their life cycle where they cannot afford to experiment with new technologies. In general, empirical studies do not find a significant or a negative effect of the age of the household head on adoption: Teklewold, Kassie, and Shiferaw (2012) find that the number of sustainable agricultural practices adopted as well as the propensity to rotate decreases with the age of the head of the household. Bokusheva et al. (2012), Ghimire and Huang (2015), and Marenya and Barrett (2007) find households with old heads engage less in technology adoption. Only Langyintuo and Mungoma (2008) find that older heads in Zambia are more likely to try out improved maize varieties.

The role of education as a catalyst for agricultural technology adoption is widely discussed in the literature, and most of the studies on technology adoption include the education level of at least the household head. Often, modern technologies are complex, requiring techniques that deviate from traditional ways of farming. Better-educated farmers are better able to process the often-abstract information and convert this knowledge into practice. All adoption studies we reviewed find a positive association between education levels and adoption. Teklewold, Kassie, and Shiferaw (2012) find that the education of the spouse also may be important as decisions about multiple sustainable agricultural practices may be taken jointly within the family in Ethiopia. Only Noltze, Schwarze, and Qaim (2012) find education not to be significant, suggesting that in Timor Leste the knowledge acquired in local primary schools may not be relevant for rice farming.

A dummy variable for the gender of the household head was also included. Agricultural extension information services, as one of the most important ways through which modern agricultural inputs and practices are promoted, are generally biased toward men. Most often, extension officers are male and target the main decision makers with respect to agriculture within households, who are also often men. Doss and Morris (2001) argue that gender-linked differences in the adoption of modern maize varieties and chemical fertilizer result from gender-linked differences in access to complementary inputs. Most studies uncover a significant negative correlation between the head of the household's being a woman and technology adoption.

Labor available to the household is also an important factor in the decision to adopt a new technology. In the context of poorly functioning labor markets, household members provide much of the work on the farm. In general, the importance of household demographics will depend on the technology modeled. For instance, household size may be more important for technologies that require substantial physical labor such as integrated natural resources management (Marenya and Barrett 2007; Noltze, Schwarze, and Qaim 2012). Less labor-dependent innovations, such as maize seed adoption, generally find no correlation with household size (Ghimire and Huang 2015; Langyintuo and Mungoma 2008). In our model, we include household size, as well as the share of female members among the total number of household members, as women often provide the largest share of agricultural labor. Apart from labor available within the household, we include a dummy to indicate whether the household also hired in labor.

Access to income from off-farm employment may ease liquidity constraints and increase the likelihood that farm households will adopt new agricultural technologies. Access to options outside of agriculture from which revenues are not perfectly correlated to agricultural output are also an effective way to hedge against common risk. On the other hand, access to off-farm income may indicate that farming is not the core business of the household, increasing the opportunity cost of technology adoption. Most studies find a positive correlation between off-farm income and agricultural technology adoption. We include access to off-farm employment as a dummy. Another factor that influences liquidity constraints is access to credit. Both Feleke and Zegeye (2006) and Mariano, Villano, and Fleming (2012) include access to credit in their models and find a positive coefficient. Teklewold, Kassie, and Shiferaw (2012) obtain a negative coefficient on a dummy that indicates the household is credit constrained.

Finally, the social network of a farmer is found to influence technology adoption (Bandiera and Rasul 2006). This is because farmers learn about new technologies not only through extension but also through observing fellow farmers and discussing agriculture-related issues with them (Conley and Udry 2010). In addition, social networks are an important risk-coping mechanism. Insofar as a new technology is perceived to be relatively more risky, the safety net provided by social capital may increase the likelihood that a household will try it out (Dercon and Christiaensen 2011). Ghimire and Huang (2015) find positive effects from being part of a farmer group. Teklewold, Kassie, and Shiferaw (2012) find positive effects of being a group member, but only on improved farming techniques such as rotation and tillage.

Institutional and Access-related Variables

Extension services are important sources of farmers' access to information. During extension visits and trainings, farmers get exposed to new technologies, and their interactions with the extension personnel stimulate communication and reflection. Especially when new technologies are involved, the advice of outside experts may be preferred to the opinions of peer farmers in social networks. Virtually all studies on the determinants of agricultural technology adoption find significant positive correlations between training and extension. For instance, Mariano, Villano, and Fleming (2012) find participation in on-farm demonstrations, attendance at trainings, and access to extension workers all have significant positive effects on the adoption of certified seed technology.

The cost of the technology, in our case the price of fertilizer, is also an important exogenous factor that will influence technology adoption. The cost of fertilizer or improved seed materials is a typical example of a variable cost related to adoption. The cost of the underlying technology is rarely included in empirical studies due to the difficulty of obtaining farmgate-level prices. Of the studies reviewed here, only Langyintuo and Mungoma's (2008) study directly includes the cost of seed in the model. Consistent with the conceptual framework, the authors find that the cost of seed affects only adoption intensity, with more expensive seeds correlated with a lower share of area planted with these seeds.

Integration into the wider market, especially links to consumer markets, is important for sustainable crop intensification to avoid Cochrane's technology treadmill. According to this theory, introducing a productivity-enhancing technology into a remote community will benefit the early adopters, as they can produce (and sell) more using the same inputs. However, more and more farmers' starting to adopt the technology results in excess supply, and output prices fall, leaving farmers often worse off than before the innovation. Links to output markets are the most effective way to increase price elasticity of demand and avoid the trap (Barrett 2008). However, access to markets is also important for acquiring some modern inputs, such as fertilizers. Recent research combining detailed production data, transport data, and panel survey data shows that nonconvex transport costs result in heterogeneity in technology adoption (Damania et al. 2016). We have therefore included three variables related to market access. First, we included distance to the nearest all-weather road as an indicator of general remoteness. Second, to capture input market integration, we have included distance to the nearest farm supply store. Finally, we included an indicator variable for market participation. All maize seed adoption studies find significant correlations with measures related to the integration within the wider market system (Ghimire and Huang 2015; Langyintuo and Mungoma 2008; Feleke and Zegeye 2006).

Agroecological Variables

The size of the plot is often considered an important factor affecting adoption decisions. In general, it is assumed that technology adoption is easier on larger plots than on smaller plots. The main argument revolves around scale economies as most new technologies will involve fixed costs, including learning costs (Feder, Just, and Zilberman 1985). This is often related to indivisibilities in the technology. For instance, oxen traction as a technological innovation compared to hoe ploughing may become feasible only if the plot is large enough. For the case of fertilizer in Uganda, there is some evidence that there are indeed issues related to indivisibilities. Small plots mean fertilizer needs to be repackaged, which often results in poor quality of fertilizer due to poor handling or adulteration (Mbowa, Kizza, and Komayombi 2015). All studies on technology adoption find a positive association with land size, except for Teklewold, Kassie, and Shiferaw (2012), where the coefficient is insignificant.

In addition to size, the quality of land may be another important factor in deciding to use inputs such as chemical fertilizers or adopting soil conservation technologies. As including soil quality indicators directly is likely to suffer from endogeneity in our fertilizer case study, we include categorical variables related to the topography of the parcel where production of potatoes takes place. Soil in valleys is most fertile, as it collects fertile topsoil from surrounding fields as a result of erosion. Plots on steep slopes are generally of lowest quality. Some of the models in the studies we reviewed here include indicators of soil quality. Both Ghimire and Huang (2015) and Langyintuo and Mungoma (2008) find that yield potential is positively correlated with maize variety adoption. Teklewold, Kassie, and Shiferaw (2012) find that both an indicator for good soil and flat top are negatively related to fertilizer use.

Independent Variable

The independent variable consists of the use of inorganic fertilizer at the plot level. While we agree organic fertilizer may be an important complement in soil nutrient management, we do not include it. This is because crop intensification through technology adoption is generally understood to involve some degree of macronutrient addition, such as nitrogen, phosphorus, and potassium.

For the independent variable in the second stage, we will use inorganic fertilizer application rates at the plot level. In particular, we obtain the amount of fertilizer in kilograms that was applied to the potato plot and divide this by the size of the potato plot. Note that this definition differs from how use intensity is measured in many of the other studies. Most studies define use intensity in terms of the proportion of land that is allocated to the new technology. However, such a definition would not be able to capture actual application density in the field: a household with 2 hectares that uses 10 kilograms on 1 acre would get a use intensity of .5. A second household with 2 hectares that uses 150 kilograms on 1 acre of land would also receive a score of .5, although it would be hard to argue their fertilizer use intensities are equal.

5. CONTEXT AND DATA

In Uganda, Irish potato (*solanum tuberosum*) production is concentrated in the southwestern highlands areas, in the districts of Kabale, Kisoro, and Kanungu, together accounting for about 47 percent of total potato production in Uganda (Van Campenhout, Bizimungu, and Birungi 2016). Potatoes are becoming an important food security and cash crop in Uganda. Potato production increased nationally from 208,000 tons in 1999/2000 to 382,000 tons in 2008/2009. Kisoro was clearly the leading district, accounting for 36 percent of total production.

The data used in this study originate from a survey conducted on a sample of farm households in the southwestern highlands for the crop season of 2013 (second) and 2014 (first). A multistage random sampling procedure was used where first 35 enumeration areas were randomly selected. Within each enumeration area, all households were listed, and it was determined whether they were growing potatoes. From these listed households that reported growing potatoes, a random sample of 500 farm households was drawn and surveyed using a standardized survey instrument on a range of socioeconomic variables. These variables included household composition, land holdings and use, assets, crop production, and consumption expenditure. In addition, detailed baseline information was collected related to potato farming, including experience, extension received, knowledge of recommended practices, and inputs and methods used. The respondents were the household heads or household principal male or female members who directly took part in decisions and managed the farms.

6. DATA PREPARATION AND DESCRIPTIVE STATISTICS

Computing Wealth Indexes by the PCA Method

The aim was to come up with a single variable that describes the asset status of the households in our sample. This single variable will then be used to divide the households into two groups depending on where they are ranked in the distribution. PCA was run on 13 selected asset indicators that are generally perceived to be important in defining asset wealth status in the study districts (Table 6.1). Among these 13 components extracted in the first stage of PCA, only the first 4 components were significant according to the Kaiser criterion[1] of an eigenvalue greater than 1.

Table 6.1 Total variance explained using principal components extraction methods using standardized values of variables

Number	Variable	Standard deviation	Scoring factor	Impact factor[a]
1	Total land area (hectares)	1.877	0.3025	1.161
2	Tropical livestock units	1.627	0.3201	0.197
3	Wheelbarrows[b]	0.295	0.3183	1.079
4	Spray pump[b]	0.389	0.3757	0.966
5	Water tank or drum[b]	0.397	0.2236	0.563
6	Storage facility/building[b]	0.444	0.2836	0.639
7	Bicycle[b]	0.464	0.2979	0.642
8	Radio[b]	0.377	0.2204	0.585
9	Car batteries[b]	0.184	0.2259	1.228
10	Television[b]	0.142	0.1948	1.372
11	Mobile phone[b]	0.439	0.2409	0.549
12	Motorcycle[b]	0.272	0.2921	1.074
13	Generator/solar[b]	0.237	0.2520	1.063

Source: Own calculations based on collected data.
Note: The tropical livestock units conversion factors used are as follows: cattle = 0.70, sheep and goats = 0.10, pigs = 0.20, and chickens = 0.01. [a]The impact factor was calculated as the score divided by the standard deviation. [b]Binary variable with 1 if household owns and 0 otherwise.

The first component was further extracted in constructing the wealth index, which explained about 25.2 percent of the total variance in the 13 indicators and gave a positive weight for all of them. The assigned weights were used to construct an overall standardized composite wealth index. Households that had wealth indexes greater than the sample mean 0 were classified as well endowed (39 percent); those with negative indexes were categorized as poorly endowed (61 percent). Dividing the score by the standard deviation generates an impact factor, which indicates the relative adjustment of the wealth index by acquiring the corresponding asset.

[1] The eigenvalue is a measure of standardized variance, with a mean of 0 and standard deviation of 1. Each of the 14 indicators contributes at least the variance of 1 to the principal components extraction. The Kaiser criterion states that unless a principal component extracts at least as much as one of the original variables (that is, has a standardized variance equal to or greater than 1), it should be dropped from further analysis (Filmer and Pritchett 2001).

Descriptive Statistics

Descriptive statistics for the variables included in the model (and justified in section 4) are provided in Table 6.2. The first variable we include is area of the potato-growing plot, expressed in hectares. We find that the average potato plot is 0.17 hectares. The distribution is somewhat skewed to the right. Among the asset poor, the mean is 0.14, while this increases to about 0.19 in the asset-rich class, and the difference is significant (two-sided t test, $p < .001$). To account for the skewedness of the distribution, we have included farm size as the logarithm in the regression models below. The age of the household head in our sample ranges from 20 to 98 years old. The overall average is about 46 years. Age of the household head does not differ significantly between the asset poor and the asset rich (two-sided t test, $p = .156$). A sizable proportion of households, about 18 percent, are headed by females. This proportion is markedly higher among the asset poor, where 1 in 4 households is headed by a female. Among the asset rich, only 1 in 10 households is headed by a female. The difference in these proportions is also significant (two-sided chi-squared test, $p < .001$).

Table 6.2 Descriptive statistics of selected variables in the empirical models

Description	All	Poorly endowed	Well endowed
Size of potato plot (hectares)	0.17 (0.15)	0.14 (0.12)	0.19 (0.18)
Age of household head in years	46.29 (15.85)	47.1 (17.22)	45.05 (13.44)
Gender of household head (1 = female)	0.18 (0.39)	0.24 (0.43)	0.10 (0.30)
Head did not complete primary education (1=yes)	0.58 (0.49)	0.68 (0.47)	0.43 (0.50)
Head has secondary education	0.20 (0.40)	0.13 (0.34)	0.30 (0.46)
Household hired in labor (1 = yes)	0.61 (0.49)	0.51 (0.50)	0.77 (0.42)
Household received extension services (1=yes)	0.38 (0.49)	0.28 (0.45)	0.53 (0.50)
Distance to nearest all-weather road	7.03 (9.26)	7.50 (9.94)	6.29 (8.07)
Distance to nearest farm supply store	6.44 (7.98)	6.44 (7.51)	6.45 (8.69)
Potato plot is on steep slope (1 = yes)	0.45 (0.50)	0.44 (0.50)	0.46 (0.50)
Potato plot is in valley (1 = yes)	0.08 (0.27)	0.08 (0.27)	0.08 (0.27)
Household has off-farm income (1 = yes)	0.69 (0.46)	0.66 (0.47)	0.75 (0.43)
Number of household members	5.12 (2.33)	4.81 (2.17)	5.60 (2.48)
Share of women in total household size (%)	0.30 (0.18)	0.31 (0.19)	0.28 (0.16)
Sold potato in market (1 = yes)	0.72 (0.45)	0.64 (0.48)	0.83 (0.38)
Member of social group (1 = yes)	0.47 (0.50)	0.49 (0.50)	0.44 (0.50)
Obtained credit in past year (1 = yes)	0.63 (0.48)	0.62 (0.49)	0.68 (0.47)
Price of fertilizer (UGX 1,000)	2.42 (0.83)	2.36 (0.73)	2.46 (0.92)
Use of inorganic fertilizer on plot (1 = yes)	0.18 (0.38)	0.14 (0.35)	0.23 (0.42)
Quantity of fertilizer used (kilograms)	5.74 (36.56)	2.89 (8.80)	9.21 (52.93)

Source: Own calculations based on collected data.
Note: Sample size differs from original sample size due to missing observations.

Next, we look at the education levels of household heads. We decided to construct three mutually exclusive categories. One category groups all the farmers who have never received any formal education; a second category consists of households in which the head has received at least some primary education. The last category groups households headed by someone who has more than only a primary education. As expected, asset-poor households are disproportionally represented in the subgroup of households with an uneducated household head, while there are relatively more asset-rich households among those headed by someone with more than primary education. Proportions of asset-rich households differ significantly between these three categories (three-sample two-sided chi-squared test, $p < .001$).

We also have data on access to extension. In particular, we asked if any member within the household has received extension on any topic or crop in the past five years. Overall, about 38 percent of households report to have received extension. Among the asset poor, this proportion is only 28 percent, while this number is 53 percent among the asset rich. Again, these proportions differ statistically (two-sided chi-squared test, $p < .001$).

The average distance to an all-weather road in our sample is about 7 kilometers, and the average distance to the closest farm supply store is about 6.4 kilometers. In both cases, these distances do not differ significantly for asset-poor and asset-rich households. Of the households, 61 percent report to be hiring in labor. Hiring in of labor occurs significantly more among the subset of asset-rich farmers (51 percent versus 77 percent, $p < .001$).

For topology, we distinguish between three mutually exclusive categories. The first one categorizes all fields that are flat. This category will be included as the reference category. We find that about 47 percent of potato-growing plots are on flat parcels. While we find that the proportion of plots on flat parcels is higher among the asset poor, the difference is not statistically significant ($p = .433$). We find another 45 percent of plots are on sloped surfaces. Also here, there does not seem to be a difference in these proportions between asset poor and asset rich ($p = .474$). Finally, a remaining 8 percent of plots are in valleys, and again, this proportion is independent of asset wealth class ($p = .895$).

Access to off-farm income is included as an indicator variable. We find that about 70 percent of households in our sample have access to off-farm income. This proportion is lower, about 66 percent, among the asset poor. It is about 76 percent among the asset rich. This difference is significant at the 5 percent significance level ($p = .034$).

We further include household size as an explanatory variable in the regressions. Overall, households consist of on average slightly more than five individuals. While usually poor households tend to be larger, we find that asset-poor households are slightly smaller than asset-rich households (t test, $p < .001$). We also include the proportion of household members who are adult females. Overall, about 30 percent of total household size is composed of adult women. This share is slightly lower in asset-rich households ($p = .084$).

We also include a measure of market access in the regression models. In particular, at the household level, we determine whether any potatoes have been sold. The vast majority of households, almost 72 percent, sold potatoes during the 2013/2014 cropping season. As expected, these percentages differ markedly between asset-poor households, where only 65 percent of households report to be selling, and asset-rich households, where 83 percent of households report to be selling in the market. The difference is significant (two-sided chi-squared test, $p < .001$).

Social capital is defined as belonging to a functioning self-help group. We find that about half of the farmers in the sample report belonging to such social groups. Somewhat surprisingly, the proportion is slightly higher among the asset poor, but the difference with the asset rich is not statistically significant (chi-squared test, $p = .237$). Credit seems to be fairly common among potato farmers: about 63 percent of farmers report having received credit in the past year. The proportion increases to almost 70 percent among the asset rich; however, the difference between the asset poor and asset rich is again not significant (chi-squared test, $p = .169$).

While it is obviously a key determinant of demand, the price of fertilizer is not included in most adoption studies. This is because it is difficult to get prices at the household level, particularly for farmers who did not adopt. We have estimated prices for fertilizer by creating a grid based on GPS coordinates and using this to impute missing values based on average prices for farmers who did buy fertilizer (and hence reported prices) in the immediate neighborhood. We find the average price for 1 kilogram of fertilizer was about UGX 2,420.

As for the dependent variables, we see that inorganic fertilizer has been used on 18 percent of a total of 1,880 potato plots. Also here, there is a significant difference between asset-poor and asset-rich farmers. Among asset-poor farmers, inorganic fertilizers have been applied to only 14 percent of plots. This figure is 23 percent among the asset rich. On average, about 6 kilograms are applied per hectare: only 3 kilograms among the asset poor but more than 9 kilograms among the asset rich. If we restrict attention to only those who report using a positive amount of fertilizer, we find that on average 30 kilograms are applied. The difference between asset poor and asset rich is much smaller now, although it is still significant ($p = .084$).

7. EMPIRICAL RESULTS AND DISCUSSION

Separate DH models were estimated for each wealth group: poorly endowed and well endowed (Table 7.1). Results of the first hurdle (probability of adopting inorganic fertilizer) are presented in the upper portion of Table 7.1, and those of the second hurdle (that is, the intensity of adoption once adopted) are presented in the lower portion.

Table 7.1 Maximum likelihood estimates of the double-hurdle model

Description	All	Asset poor	Asset rich
	Used fertilizer on plot (1 = yes)		
Log(plot size in hectares)	0.172*	0.423***	0.119
	(0.069)	(0.124)	(0.080)
Age of household head (years)	–0.006	–0.005	–0.011
	(0.005)	(0.008)	(0.008)
Gender of household head (1 = female)	–0.944**	–1.520*	–0.459
	(0.345)	(0.687)	(0.361)
Head has no formal education (1 = yes)	0.270	0.276	0.339
	(0.209)	(0.389)	(0.227)
Head has secondary education (1 = yes)	0.094	–0.047	0.247
	(0.248)	(0.466)	(0.280)
Received extension (1 = yes)	–0.233	–1.445***	0.069
	(0.180)	(0.351)	(0.194)
Distance to nearest all-weather road (kilometers)	–0.014	–0.010	–0.012
	(0.012)	(0.016)	(0.014)
Distance to nearest farm supply store (kilometers)	–0.017	–0.078*	–0.015
	(0.014)	(0.030)	(0.013)
Hired in labor (1 = yes)	0.522*	0.141	0.593
	(0.212)	(0.289)	(0.327)
Plot on steep slope (1 = yes)	–0.515***	–0.720***	–0.425**
	(0.122)	(0.188)	(0.156)
Plot in valley (1 = yes)	–1.006***	–0.612	–1.010***
	(0.248)	(0.625)	(0.290)
Has off-farm income (1 = yes)	–0.013	0.281	–0.202
	(0.173)	(0.264)	(0.224)
Household size (number of members)	0.111**	0.106	0.119**
	(0.036)	(0.071)	(0.045)
Share of women in household (%)	0.534	0.892	0.852
	(0.496)	(0.772)	(0.696)
Sold potato in market (1 = yes)	1.198***	1.587***	0.989*
	(0.269)	(0.389)	(0.407)
Member of social group (1 = yes)	0.0512	0.533	–0.173
	(0.225)	(0.460)	(0.265)
Obtained credit in past year (1 = yes)	–0.142	–0.455	0.065
	(0.224)	(0.482)	(0.267)
Price of fertilizer (UGX 1,000)	0.104	–0.426**	0.258*
	(0.098)	(0.138)	(0.105)
Constant	–3.458***	–2.281*	–3.578***
	(0.728)	(1.141)	(1.024)

Table 7.1 Continued

Description	All	Asset poor	Asset rich
	Log(quantity of fertilizer used on plot [kilograms per hectare])		
Log(plot size in hectares)	–0.479***	–0.077	–0.592***
	(0.103)	(0.144)	(0.117)
Age of household head (years)	0.005	0.002	0.007
	(0.008)	(0.011)	(0.014)
Gender of household head (1 = female)	0.627	0.905***	0.411
	(0.389)	(0.254)	(0.761)
Head has no formal education (1 = yes)	–0.457*	–0.594*	–0.336
	(0.193)	(0.238)	(0.293)
Head has secondary education (1 = yes)	–0.306	–0.618	–0.274
	(0.279)	(0.345)	(0.380)
Received extension (1 = yes)	–0.055	–0.072	–0.155
	(0.187)	(0.264)	(0.268)
Distance to nearest all-weather road (kilometers)	–0.015	–0.018	–0.018
	(0.014)	(0.012)	(0.025)
Distance to nearest farm supply store (kilometers)	0.004	–0.063	0.014
	(0.007)	(0.036)	(0.009)
Hired in labor (1 = yes)	0.023	–0.389	–0.332
	(0.311)	(0.257)	(0.506)
Plot on steep slope (1 = yes)	–0.354*	–0.378	–0.435
	(0.170)	(0.204)	(0.254)
Plot in valley (1 = yes)	–0.871**	–2.295***	–0.416
	(0.332)	(0.608)	(0.263)
Has off-farm income (1 = yes)	–0.477**	–0.507	–0.281
	(0.184)	(0.409)	(0.320)
Household size (number of members)	0.022	0.091	0.002
	(0.038)	(0.067)	(0.055)
Share of women in household (%)	0.347	0.139	–0.301
	(0.445)	(0.654)	(0.762)
Sold potato in market (1 = yes)	–0.147	–0.160	0.121
	(0.251)	(0.367)	(0.250)
Member of social group (1 = yes)	–0.460	–0.419	–0.355
	(0.249)	(0.332)	(0.370)
Obtained credit in past year (1 = yes)	0.705*	0.510	0.684
	(0.295)	(0.369)	(0.419)
Price of fertilizer (UGX 1,000)	–0.290***	–0.055	–0.410***
	(0.064)	(0.127)	(0.074)
Constant	3.165***	4.057***	3.121***
	(0.548)	(1.091)	(0.833)
Sigma	0.747***	0.437***	0.820***
	(0.063)	(0.042)	(0.071)
N	1,554	812	742

Source: Own calculations based on collected data.

Note: Standard errors, adjusted for clustering at the household level, are in parentheses. Sample size used in estimation may differ from original sample size due to missing observations that were dropped. Significance denoted as: *$p < .05$. **$p < .01$. ***$p < .001$.

Factors Influencing the Probability of Adopting Fertilizer

In this section, we present the results of our analysis from the first hurdle (decision about whether to adopt fertilizer in potato production) presented in the upper part of Table 7.1. In the second column of the table, we present coefficient estimates for the entire sample. In the third column, results are displayed for the subsample of asset-poor farmers, while in the last column of the table we show results for asset-rich farmers. Corresponding to these estimates, marginal effects are provided in the top panel of Table 7.2.

Table 7.2 Marginal effects

Description	All	Asset poor	Asset rich
	Used fertilizer on plot (1 = yes)		
Log(plot size in hectares)	0.038*	0.061***	0.029
	0.015	0.017	0.022
Age of household head (years)	–0.001	–0.001	–0.003
	0.001	0.001	0.002
Gender of household head (1 = female)	–0.208*	–0.221*	–0.110
	0.086	0.103	0.104
Head has no formal education (1 = yes)	0.059	0.040	0.081
	0.049	0.070	0.071
Head has secondary education (1 = yes)	0.021	–0.007	0.059
	0.058	0.081	0.073
Received extension (1 = yes)	–0.051	–0.210***	0.017
	0.040	0.059	0.054
Distance to nearest all-weather road (kilometers)	–0.003	–0.001	–0.003
	0.003	0.003	0.006
Distance to nearest farm supply store (kilometers)	–0.004	–0.011	–0.004
	0.005	0.006	0.007
Hired in labor (1 = yes)	0.115*	0.020	0.143
	0.053	0.047	0.093
Plot on steep slope (1 = yes)	–0.113***	–0.104***	–0.102*
	0.026	0.029	0.042
Plot in valley (1 = yes)	–0.222***	–0.089	–0.243**
	0.062	0.066	0.084
Has off-farm income (1 = yes)	–0.003	0.041	–0.048
	0.041	0.043	0.066
Household size (number of members)	0.025**	0.015	0.029*
	0.008	0.012	0.012
Share of women in household (%)	0.118	0.130	0.205
	0.118	0.123	0.197
Sold potato in market (1 = yes)	0.264***	0.231***	.238**
	0.068	0.069	0.089
Member of social group (1 = yes)	0.011	0.077	–0.041
	0.052	0.076	0.075
Obtained credit in past year (1 = yes)	–0.031	–0.066	0.016
	0.053	0.088	0.076
Price of fertilizer (UGX 1,000)	0.023	–0.061*	0.062*
	0.024	0.025	0.028
	Log(quantity of fertilizer used on plot [kilograms per hectare])		
Log(plot size in hectares)	0.017	0.165	–0.042
	0.053	0.089	0.072
Age of household head (years)	–0.003	–0.002	–0.007
	0.004	0.011	0.009
Gender of household head (1 = female)	–0.490*	–0.504	–0.246
	0.255	0.417	0.392
Head has no formal education (1 = yes)	0.085	0.029	0.175
	0.154	4.396	0.220
Head has secondary education (1 = yes)	0.001	–0.109	0.121
	0.194	0.765	0.294
Received extension (1 = yes)	–0.162	–0.614*	0.017
	0.136	0.305	0.184
Distance to nearest all-weather road (kilometers)	–0.012	–0.007	–0.013
	0.009	0.025	0.020
Distance to nearest farm supply store (kilometers)	–0.010	–0.042	–0.008
	0.016	0.082	0.020
Hired in labor (1 = yes)	0.343	0.003	0.362
	0.179	18.630	0.374

Table 7.2 Continued

Description	All	Asset poor	Asset rich
	Log(quantity of fertilizer used on plot [kilograms per hectare])		
Plot on steep slope (1 = yes)	–0.404***	–0.355	–0.406**
	0.092	0.866	0.141
Plot in valley (1 = yes)	–0.825***	–0.587	–0.831**
	0.211	0.535	0.309
Has off-farm income (1 = yes)	–0.103	0.044	–0.209
	0.126	2.234	0.230
Household size (number of members)	0.076**	0.057	0.088*
	0.026	0.135	0.040
Share of women in household (%)	0.415	0.392	0.558
	0.357	0.609	0.659
Sold potato in market (1 = yes)	0.75***	0.639	0.751*
	0.196	0.424	0.310
Member of social group (1 = yes)	–0.057	0.162	–0.204
	0.169	1.692	0.269
Obtained credit in past year (1 = yes)	0.046	–0.116	0.198
	0.175	0.365	0.266
Price of fertilizer (UGX 1,000)	0.010	–0.185	0.099
	0.068	0.806	0.086
N	1,554	812	742

Source: Own calculations based on collected data.
Note: Standard errors, generated through bootstrap based on 500 replications and adjusted for clustering at the household level, are in parentheses. Sample size used in estimation may differ from original sample size due to missing observations that were dropped. Significance denoted as: $*p < .05$. $**p < .01$. $***p < .001$.

Overall, pooling the asset poor and asset rich in the second column, we find that the significant variables have the expected sign. We find that the plot size is indeed positively correlated to the propensity to adopt fertilizer. A doubling of plot size is associated with a 3.2 percent higher likelihood of inorganic fertilizer adoption. Female-headed households have on average a 20 percent lower probability of adoption; we also find that households that report hiring in labor are more likely to use fertilizer. For topology, the reference category is flat plots, where it indeed makes most sense to apply fertilizer. On steep plots, fertilizer runoff is a problem, and as we see, farmers with such plots are significantly less likely to use fertilizer. Valleys, on the other hand, have high inherent fertility. As such, relative to flat plots, fertilizer is also less likely to be applied to plots in valleys. The size of the coefficient is important, suggesting a 22 percent lower probability of using fertilizer in valleys. Household size is positively related to fertilizer adoption. Finally, a more commercial attitude, as evident by having sold potatoes, is also correlated to fertilizer adoption. Farmers who report participating in the market are more than 26 percent more likely to use fertilizer.

More interestingly, there are substantial differences between asset-poor and asset-rich farmers in the factors correlated to fertilizer adoption, as can be seen by comparing the third and fourth columns in the top panels of Tables 7.1 and 7.2. For instance, the effect related to the size of the plot stems completely from the asset-poor farmers. A doubling of plot size corresponds to an increase in the probability of adoption by about 6 percentage points. For asset-rich farmers, the size of the plot seems to be unrelated to the decision to adopt fertilizer. Apparently, fixed costs related to fertilizer adoption pose a problem only for the asset poor. One likely explanation consistent with qualitative findings and other research is that this is due to indivisibilities in fertilizer and the risk of decreasing quality when fertilizer is repackaged into smaller quantities. In this case, asset-poor farmers will not adopt if their plots are too small and they have to recur to repackaged fertilizer of uncertain quality. For asset-rich farmers with small plots, the risk of buying poor-quality fertilizer poses less of a barrier to fertilizer use, as they have sufficient assets to insure against this risk. An alternative explanation would be that asset-poor farmers simply cannot afford to experiment on their small plots as they have few alternatives to fall back on should things go wrong.

Similarly, the gender effect should be ascribed entirely to the asset-poor subgroup. In households that have access to sufficient productive assets, female-headed households are equally likely to adopt inorganic fertilizer as are male-headed households. This finding confirms that of Doss and Morris (2001), who claim that gender-linked differences in the adoption of modern maize varieties and chemical fertilizer result from gender-linked differences in access to complementary inputs. It is also consistent with Marenya and Barrett (2007), who find that the coefficient on the gender of the head becomes very small if one controls for nonfarm income and livestock holdings that are strongly correlated with the gender of the household head. In other words, it is not gender per se that gives rise to adoption patterns where women seem to adopt less but the resource inequities that usually go with gender and bite especially in asset-poor households.

Distance to the nearest farm supply store is significant only for asset-poor farmers. The farther the nearest supply store, the lower is the chance that the asset-poor farmer will adopt fertilizer. Table 7.2 shows that an extra kilometer away from the farm supply store reduces the likelihood of adoption by 1.1 percentage points. For asset-rich farmers, the distance to the nearest farm supply store does not seem to matter. This is probably because asset-rich farmers have other assets that can support them in sourcing fertilizer. For instance, they may have easier access to cars enabling them to buy fertilizer in towns, making them less dependent on small, nearby supply stores. This finding is in line with Langyintuo and Mungoma (2008), who also point out the importance of local retail stores for asset-poor farmers' adoption of improved seed.

The coefficient on the dummy indicating whether the household hired in labor becomes insignificant when we confine ourselves to asset-poor farmers. This coefficient was significantly positive in the full sample, and it is still significant at the 10 percent level in the sample of asset-rich farmers. Apparently, households that obtain labor from the market are also about 14 percent more likely to apply fertilizer. However, if households are resource constrained, there is no difference in the likelihood of adoption between those that hire in labor and those that do not. We find a similar effect for household size, with each extra member associated with a 3 percent increase in the adoption probability among the asset rich. This suggests important complementarities between assets and labor requirements among fertilizer users.

Another particularly interesting finding relates to the price of fertilizer. While we do not find a significant effect in the sample as a whole, we find that high fertilizer prices discourage asset-poor farmers' adoption. However, among asset-rich farmers, we find that higher fertilizer prices increase adoption. This may be consistent with a market characterized by goods that differ in quality and asymmetric information, whereby the price is used to signal quality. Recall that asset-poor and asset-rich farmers seem to obtain fertilizer from different sources. While fertilizer in rural supply stores of generally lower quality compete on price, wholesalers may use prices to signal superior quality.

Finally, there is the disturbing finding that extension actually seems to discourage asset-poor farmers' adoption of inorganic fertilizer. Farmers in the asset-poor group are significantly less likely to adopt fertilizer if they received extension services. The effect is substantial in size: asset-poor households that received extension report a 21 percent lower probability of using fertilizer. Among the group of asset-rich farmers, extension has no significant effect. One scenario consistent with this result is that extension workers warn farmers against "wasting" fertilizers, pointing out the many complementary inputs needed to make fertilizer adoption profitable. For instance, extension workers may point out the importance of appropriate water supply when using fertilizer. This may discourage asset-constrained farmers who would have otherwise adopted.

Factors Related to Adoption Intensity

While the first hurdle models the decision to adopt, the second hurdle looks at the adoption intensity conditional on the decision to adopt. As these decisions are sequential and may be affected differently by the determinants, it is instructive to compare results from the first to the second hurdle. Also here, the most interesting cases will be the ones that have different coefficient estimates. In fact, when comparing results for the entire sample (second column) only half of the variables have the same effect (in terms of significance [yes/no] and direction [positive/negative]) in both stages. In fact, if we confine ourselves to only significant effects, only the topography of the plot has the same effect in both stages of the decision process: fertilizer is less likely to be used on plots in valleys and plots on steep slopes, and if fertilizer is used, less of it is used on plots in valleys and plots on steep slopes. This underscores the importance of using a DH model to investigate adoption. In general, significant effects in the first hurdle are related to fixed costs that need to be overcome, while those in the second hurdle point to variable costs as binding constraints.

The first interesting difference here is related to plot size. From the first hurdle, we know that the larger the plot, the more likely it is that fertilizer is applied. However, if fertilizer is used, it is less intensively applied on larger plots. We have seen that a doubling of plot size increases the adoption probability by about 3.8 percentage points. We see in the second panel of Table 7.1 that a doubling of plot size reduces the quantity used on the field by about 30 percent among those who are using fertilizer. Especially when a variable has countervailing effects such as in this case, it is instructive to look at the unconditional partial effects reported in the lower panel of Table 7.2. From this we conclude that the overall effect of plot size on adoption intensity is not significantly different from zero.

There are various possible explanations for this observed pattern. For example, it may be that larger plots are inherently more fertile, so less fertilizer is needed. More likely, this is a case where indivisibilities affect variable costs, whereby households with small plots are forced to buy larger quantities than they actually need. However, the result is reminiscent of the inverse farm size–productivity relationship, one of the oldest puzzles in development economics, so the relationship may be spurious (Barrett, Bellemare, and Hou 2010). In particular, the negative correlation may be due to the technical feature that farm size is included on both sides of the equation, once as the denominator in the use intensity measure and once as an explanatory variable. In the context of such "linked variables," measurement error in plot size results in a negative correlation.

The gender of the household head seems to differ between the two hurdles. While female-headed households are less likely to engage in adoption, there seems to be no difference in the quantities applied conditional on having adopted fertilizer between male- and female-headed households. This result suggests that female-headed households' adoption of inorganic fertilizer on potatoes is constrained mainly by fixed costs and less related to variable costs. Judging by the unconditional partial effect, fertilizer adoption rates are only about 61 percent of (geometric) average rates for male-headed households.

The reverse pattern is found for education. Compared to farm households with a household head who has finished primary education, farm households with a household head who has no education are equally likely to adopt fertilizer. However, the disadvantage of having no education seems to become important when the decision about how much fertilizer to apply has to be taken. According to the bottom part of Table 7.1, among those that do adopt fertilizer, households with uneducated heads apply on average only about 56 kilograms per hectare, as opposed to households that have a head with a primary education, which apply on average about 89 kilograms per hectare. This seems to suggest that education levels affect knowledge about appropriate dosage levels.

Labor, as proxied by both hired-in labor and household size, also relates differently in the second hurdle than in the first hurdle. In the first hurdle, labor availability seems to be a significant barrier to adoption. However, once the hurdle has been taken, additional labor does not seem to affect adoption intensity. It thus seems that the bottleneck in terms of labor identified above is not related to the application of fertilizer in itself but may be related to the fact that additional labor is needed regardless of the quantity applied. For instance, when fertilizer is used, more time may be needed for a range of activities such as procurement, supervision, transport, and weeding, which may be less dependent on actual quantities applied.

The finding that selling potatoes in the market is positively and strongly related to fertilizer adoption but not related to the quantity used also points to significant fixed costs for those not participating in the market. This may be because farmers who are better integrated into the market system face a lower cost to access farm inputs, for instance, due to the possibility of back-loading when they visit the market to sell produce. However, market participation status is unlikely to affect the marginal cost of additional quantities of fertilizer. More in general, market participation is an important pull factor that reduces the risk that the farmer gets stuck with excess produce. This interpretation is in line with the finding that the effect is especially strong among asset-poor farmers. Taken together, the effect from the first stage is strong enough to render a significantly positive unconditional effect (Table 7.2): overall, market participation is associated with a more than doubling of quantities of fertilizer used.

Access to credit does not influence adoption in the first stage, but there is some evidence that liquidity is important for the decision related to quantities. Finally, the price of fertilizer becomes significant. An increase in the price of UGX 1,000 reduces the quantity applied by about one-quarter. Both of these findings are consistent with the interpretation of the second hurdle as mainly modeling fixed costs.

Just as in the first hurdle, we differentiate between asset-poor and asset-rich farmers in the second hurdle. Also at this stage in the decision-making process, we find that the determinants of the quantity of fertilizer used often differ between the asset poor and the asset rich.

The negative coefficient for plot size in the entire sample stems mainly from the asset-rich farmers. Apparently, on larger farms in the asset-rich group, there seems to be some dilution wherein fertilizer is spread over larger areas. This dilution is not witnessed among asset-poor farmers, which may be due to the combination of bulkiness in fertilizer inputs and small plot sizes (and little variation in plot size) among this group. In addition, if we assume that people with larger plots of land are more likely to be less accurate in their estimates of the size of the plot, this finding supports the hypothesis that the relationship is spurious and caused by the linked-variables problem alluded to above.

While overall, the gender of the household head seems unrelated to the quantity of fertilizer applied on the field, we do find that among fertilizer users in the asset-poor category, female-headed households use on average more fertilizer than male-headed households. The effect is strong and sizable: within the group of asset-poor fertilizer users, the amount of fertilizer used by male-headed households is on average 109 kilograms per hectare, while this is about 270 kilograms per hectare among female-headed households in this group.

The education effect also differs between asset-poor and asset-rich farmers in the second hurdle. For asset-poor farmers, being uneducated is associated with lower quantities applied. The fact that education level affects variable costs only among the asset poor may suggest this is related to complementary tools that facilitate dosage. Asset-poor uneducated farmers have difficulties interpreting complex dosage instructions and have no practical aids to assess the correct quantities, leading them to spread the fertilizer too thin because of cost considerations. Farmers with access to complementary assets may have tools such as measuring cups that help in dosing fertilizer. With respect to topography, the effect on quantity used seems to come mainly from the asset-poor category of farmers. Asset-poor farmers who farm in valleys use significantly less fertilizer than asset-rich farmers. The price effect, on the other hand, seems to accrue mainly to asset-rich farmers.

Finally, instead of comparing asset-poor to asset-rich farmers in each hurdle separately or comparing the two hurdles for the entire sample, it is instructive to compare heterogeneity in adoption decision to heterogeneity in adoption intensity. The most striking finding here relates to female headedness.

Female-headed households are less likely to adopt fertilizer. This effect comes entirely from the asset-poor group, suggesting that the decision of female households not to adopt is due to a lack of access to assets. Interesting to note, we find that, once these asset-poor female-headed households decide to use fertilizer, they apply it at a significantly higher rate than male-headed asset-poor households. The results are also consistent with Beaman et al. (2013), who find that women who receive fertilizer both use more fertilizer and use more complementary inputs such as herbicides and hired labor. It is also consistent with Vorley et al. (2015), who find that female-headed households are less likely to participate in oilseed value chains in Uganda. However, once they participate, their engagement (measured by the proportion of land allocated to oilseeds) is not significantly different from that of male-headed households (in fact they allocate a larger proportion of land, but this is not significant as there are few participating female-headed households). It suggests that the lack of access to complementary assets, risk-absorbing assets, or both by women constitutes a large fixed cost. Overcoming this barrier would significantly increase adoption intensity.

8. CONCLUSIONS AND POLICY IMPLICATIONS

In Uganda, and in Africa south of the Sahara in general, agricultural yields are low. Increasing population pressure and changing diets means these yields need to increase substantially, such that more food can be grown on the same area without putting further stress on the environment. One important ingredient in such a Green Revolution for Africa is the use of modern inputs and adoption of recommended practices, such as inorganic fertilizer and irrigation. Low rates of modern input use and technology adoption in many countries, including Uganda, mean there is substantial room for improvement in yields. As the majority of farmers in Africa are poor smallholders in rural areas, increasing productivity is also likely to have substantial welfare effects.

This study used the case of Ugandan potato farmers to study adoption of synthetic fertilizer. The aim was to uncover correlations that can help design policies that target incentives for fertilizer adoption. Therefore, we correlated a range of plot-level, household-level, and institutional-level characteristics to adoption behavior. However, as the decision to adopt inorganic fertilizer is more related to fixed costs while the decision about how much fertilizer to apply is more related to variable costs, we modeled adoption as a sequence of decisions. In addition, as the households' access to productive assets is likely to interact (in potentially nonlinear ways) with these characteristics, we estimated separate models for asset-rich and asset-poor farmers.

The fact that we found considerably different parameter estimates between the propensity to adopt and use intensity, and between asset-rich and asset-poor farmers, shows that our estimation strategy was warranted. We found, among other things, that asset-poor female-headed households were less likely to adopt fertilizer. However, if they decided to adopt fertilizer, they used on average more kilograms per hectare than male-headed households. Adoption seemed to be positively correlated to plot size, but only so among the asset poor. We also found differential effects between asset-poor and asset-rich farmers for labor. One of the most striking findings was lower fertilizer adoption among farmers who received extension information. However, this was only the case for asset-poor farmers. The findings lead to a range of policy recommendations.

First, various findings, such as the fact that the asset poor were less likely to use fertilizer on small plots, point to issues related to indivisibilities. Standard fertilizer bags of 25 kilograms prevent farmers from experimenting on small plots. In addition, poor handling and storage as well as adulteration when fertilizer is repackaged into quantities that are better adapted to small farmers are documented problems in Uganda (Mbowa, Kizza, and Komayombi 2015). One way to deal with this is to increase quality control and punish fertilizer vendors who sell low-quality fertilizer. However, this is likely to be costly in terms of policing, and a repressive approach may have various unwarranted side effects. For instance, if quality deterioration is due to poor storage instead of willful adulteration, the risk of being punished may deter farm supply stores from storing and selling fertilizer altogether. A better approach therefore would be to encourage manufacturers to produce fertilizer in appropriately sized packages such that repackaging is not necessary anymore. Alternatively, farmers could be encouraged to pool their plots, such that fixed costs can be spread over larger areas. However, this may require cooperatives or farmer groups, which are often difficult to sustain.

The negative correlation between plot size and the likelihood of adopting may also mean asset-poor farmers cannot afford to experiment on their small plots, as they have few alternatives to fall back on should things go wrong. Providing free or subsidized fertilizer thus may not suffice. Here, demonstration plots may be used to show the effect of fertilizers to farmers who do not have the space to experiment. However, demonstration plots are often managed by model farmers or experts, and asset-poor farmers may have a hard time identifying with such farmers. An alternative therefore could be providing fields where farmers can experiment with new technologies.

Second, we found that education is not relevant in the decision to apply fertilizer but becomes important when the decision about how much to apply is taken. This suggests that less educated people may have trouble uncovering correct application rates. Interventions aimed at increasing awareness of application rates may therefore be effective. Examples include clear instructions on packages that can be understood by illiterate farmers. However, due to repackaging in smaller quantities, these instructions often get lost with the original packaging material. Therefore, materials of a more public nature, such as posters in public places and in farm supply stores, may be necessary. In addition, the fact that this finding is conditional on asset status may suggest complementary assets are important. The provision of measuring tools may therefore also be an effective intervention. For instance, encouraging results emerge from ongoing research about providing special spoons (BlueSpoons) that can be used for easy and correct dosing of fertilizer in Kenya (Duflo, Kremer, and Robinson 2016).

Third, we uncovered important gender-related effects where asset-poor female-headed households are less likely to engage in fertilizer adoption. However, we find that these same households are likely to use more fertilizer per hectare of land once the decision to use fertilizer has been taken. This suggests that supporting women with complementary assets and helping them overcome fixed costs related to technology adoption may have potentially important multiplier effects. In particular, providing access to mechanization to women to reduce the burden of agricultural labor is likely to increase fertilizer uptake. Risk-reducing interventions, such as the promotion of women's groups and the development of insurance products targeting women, are also likely to be effective.

Fourth, we found that access to fertilizer is a significant fixed cost for asset-poor farmers. Asset-poor farmers who are farther away from farm supply stores are less likely to adopt fertilizer. The availability of a nearby fertilizer sales point seemed less relevant to asset-rich farmers. As such, an extensive network of rural farm supply stores is needed to increase adoption among the asset poor. In remote places where supply stores are commercially not viable, distribution of fertilizer by public extension systems may be warranted.

Fifth, we found that exposure to extension workers actually reduces the propensity to adopt fertilizer. We conjecture this may be due to extension workers' putting too much emphasis on the need for complementary inputs when adopting fertilizer, scaring away asset-poor farmers from adopting. Extension workers should be wary of discouraging farmers from using fertilizer by pointing out the need for complementary assets and inputs. They should be trained in providing low-cost alternatives for complementary productive assets. In addition, they should have a clear idea of the relative importance of each complementary asset and be clear about this to the farmers.

Sixth, the opposing effects of the price of fertilizer on technology adoption suggest that in this particular case, fertilizer subsidies may be viable. Due to the fact that poor farmers perceive the cost of fertilizer as an important fixed cost, reducing the price may increase adoption among the group. At the same time, due to signaling of quality through price, asset-rich farmers seem to prefer more expensive fertilizer. Therefore, fertilizer subsidies may be self-targeting, benefiting the asset poor proportionally more than the asset rich. Still, targeting by a central planner may be necessary, as asset-rich farmers do seem to be sensitive to prices with respect to quantities applied conditional on adoption, leaving room for overuse.

Seventh, we have seen what a powerful pull factor market access can be. Integrating rural areas into the wider market system, by cultivating market links to consumer centers both within Uganda and in the wider region, provides important incentives to farmers to crank up their productivity. Investment in rural infrastructure and marketing mechanisms will improve access to farm input and output markets, hence encouraging sustainable use of fertilizers.

We found that labor constraints affect the fixed costs related to fertilizer adoption, albeit only among asset-rich farmers. It is unclear why asset-poor farmers seem unable to translate additional labor into an increase in adoption, suggesting labor affects fixed costs differently among these farmers. More research is needed to find why this is so.

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